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A case for agent-based models in organizational behavior and team research

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Abstract
Purpose – This paper aims at introducing agent-based models (ABMs) and reviews some of their features in an attempt to show why they can be useful for organizational behavior research.

Design/methodology/approach – The use of simulations has increased substantially in the past ten to fifteen years, but management seems to hold back to the agent-based "revolution". The paper first describes the ABMs, and then discusses some of the issues that usually prevent management scholars from using simulations.

Findings – This paper indicates how an agent-based approach can help overcome the hesitations surrounding computer simulations because (a) it makes it relatively easy to model emergent and complex social phenomena, and (b) simulation is made easier by user-friendly software platforms that connect it to the existing research methods.

Originality/value – This article describes ABMs in a way that may be attractive to organization scholars, and it depicts the frontiers of a more flexible computational and mathematical approach to organizations, management and teams.

Keywords Research, Measurement

Paper type Viewpoint

1. Introduction
This article is concerned with introducing the opportunities and advantages that agent-based modeling and simulation may bring to management and organization studies. Team and group research is one of the most promising areas for this particular method, and I will be referring to it throughout the article.

What do the scientific domains of Medicine, Biology and Sociology have in common? As with every scientific discipline, they share the common goal of producing results that benefit human beings and their societies. This however is too broad an answer. There is no need to point at how findings shared across disciplines may work toward the improvement of human conditions either, as it may be too hard to prove and may be too speculative. If one looks at the surface of what these domains cover, it is apparent that

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each has one or more specific sub-discipline that focuses mainly on quantitative and mathematical methods. For example, epidemiology, theoretical biology and mathematical sociology apply advanced modeling techniques to better understand, refine and/or develop theory. This approach has been extremely successful in these scientific domains.

When we turn our attention to management and organization behavior, the picture is different. In the past two decades (1994-2013), the top ten management journals, ordered by their five-year impact factor (ISI Thompson's Journal Citation Report 2013)[1], published 159 articles (mean = 15.9, SD = 13.8) where "mathematical model" (and variants) appears as a subject term. This quick search may not be indicative, as there are journals that pay more attention to theory development (e.g. *Academy of Management Review*) and others that are more evidence-based (e.g. *Journal of Applied Psychology*). While the absolute number (i.e. 159) may suggest a substantial body of literature, it only forms 1.2 per cent relative to the total number of articles published in these journals over these past two decades. If we switch our attention to the word "simulation", there are 79 hits representing 0.6 per cent of the total number of articles published. The only caveat is that the subject terms may not always be indicative of the actual content of the article. Nevertheless, the question is not whether management has a highly math-oriented branch – it does, if we look at the tradition of operations research/management[2], and it does not, if we are looking for something like "mathematical management" – but whether it may benefit from it. Given that all will concur that 1.2 per cent (or 0.6 per cent) of published articles on the subject matter is not a significant achievement, a more interesting question to ask is why do most management scholars not consider quantitative computational techniques as a complementary tool to advance their discipline? If we turn our attention to journals that focus on team and group research, we find a similar picture[3]. Combinations of "mathematical model" appears as a keyword for about 26 times (0.8 per cent) and "simulation" is used for about 27 times (0.9 per cent). The question on the lack of attractiveness of simulation techniques attracts even more interest if we reflect on the fact that a computer simulation article by Cohen *et al.* (1972), the so-called "garbage can" model, remains one of the seminal contributions of this field, showing that these approaches can prompt non-trivial insights (Fioretti and Lomi, 2010).

There are several reasons that can be brought in to explain why this has happened. I speculate that the most relevant are reducible to the following four, and are reported in no particular order. First, simulations in management and organization studies aim at representing complex social phenomena (Lave and March, 1975; Mollona, 2008). This aim is a clear challenge in that organizational-related variables are many and their behavior is difficult to predict, ambiguity being one of the most apparent characteristic (March, 1981). Most importantly, variability is only partially reproducible in a virtual experiment, such as a computer simulation. The computational model (any model) is, by definition, a partial representation of reality because it simplifies it to represent some of its salient characteristics. This aspect has always raised suspicion among scholars, and the overall "feeling" is that computational models aim too high and remain too simple.

A second reason, connected to the first, is that computer simulations remain an artificial representation of reality and that their link to real phenomena rests on the interpretation that a given modeler gives to virtual elements (Gilbert and Troitzsch, 2005). Of course, interpretation is always a subject to fantasies or erroneous accounts.

To overcome this problem, some simulation modelers create rather complex representations of reality, and this sometimes ends up hindering the message of the research effort.

Third, the skills and knowledge involved in modeling are considered a plus by management scholars, something that is outside their traditional methodological "toolbox". This has always been a particularly serious concern in that there are particular languages or math software programs that need to be mastered to produce appropriate representations (Fioretti, 2013). Given what is considered in the aforementioned points, there has always been reluctancy to invest time and efforts on something that may produce uncertain results.

Finally, the fourth problem is that the role of simulations in social science is perceived as unclear. For example, are simulations useful in relation to theory development, or are they tools to further validate quantitative findings?

These four concerns that simulation studies have faced serve to clarify why they have not yet taken off. However, the overall landscape of computational methods, available since the early days of computer simulation (Lave and March, 1975), has recently been transformed. This means that some of the problems, usually identified as challenging, need some serious re-definition. This article shows how agent-based models (ABMs) attempt to provide a partial coverage to most of the concerns raised on simulation studies. In the following, I review each one of the four concerns and show how ABMs can be looked at as one of the possible future direction for computer simulation in our fields. I then review the sources that make this technique increasingly popular, and then present a few concluding remarks. Before addressing these points, the next section shortly describes this technique.

2. What is agent-based modeling?

A consensus about how to define agent-based simulation has yet to be reached. This is probably a result of its malleability and adaptability. Scholars do however agree on a few important points. ABMs are computational models (Gilbert, 2008; Goldstone and Janssen, 2005) in that modelers program software applications instruct a computer that performs specific operations. The unit of the model is the agent, an autonomous "individual" who behaves in a given environment (or space) according to established rules.

2.1 The agent

The characteristic that best describes ABMs is the agent. As models are simplified representations of events and/or phenomena, they reproduce what researchers think are the most significant features of a given phenomenon (Gilbert and Troitzsch, 2005). The agent is the elementary unit through which the object of research is analyzed. For the social scientist, an agent could be, for example, an organization that adopts an innovation (Antonelli and Ferraris, 2011; Dunn and Gallego, 2010; Pajares *et al.*, 2003), or a consumer who buys a product (Zhang and Zhang, 2007) or an employee making a decision about whether to strike or not. Management and social scientists who use ABMs interpret and model agents via two characteristics: autonomy and interactivity.

Each agent is autonomous because it has unique individual characteristics. For example, an ABM could model individual perceptions of social responsibility, assigning a value to each agent as to represent real data (Okada, 2011). Or, data can be distributed following a random-normal or any other distribution. There is no limit to the attributes of each agent, and there is no limit as to what agents share. For example, it may be that scholars would like to model a certain aspect of organizational culture (Groeber *et al.*, 2009) in a way that each agent shows some independent understanding of a shared concept (Axelrod, 1997a). In short, each agent can "deal" with a specific aspect of culture; hence, the value that represents culture can be standardized for every agent.

A second aspect is that agents interact with each other. These dynamics can follow specific rules (see below), and/or they can emerge from the system. Some degree of randomness can be built in the system so that interactions with other agents modify the perception that each agent has of itself and of its surrounding world. For example, this is what simulated contingent workers do in Ekmekci and Casey's (2011) model of organizational identification. Interaction is particularly relevant for the study of team dynamics, where dyadic or more complex exchanges among members provide potentially insightful views. Another peculiar feature of an ABM is that agents can be modeled in a way so they can only "see" what surrounds them, without knowing what goes on at the system level. This meets more realistic expectations. In fact, it is unrealistic to hypothesize that every employee (or team member) has the same links, interactions and knowledge of all the other employees within the entire company. It is likely that employees are more familiar with the team or the department within which they work (Secchi and Gullekson, 2012). Hence, they have stronger interactions with other employees affiliated to those teams and departments (Dunin-Keplicz and Verbrugge, 2010).

2.2 The environment

Agents interact in a limited space. The environment takes the form of a multi-dimensional area where agents are located (Gilbert and Terna, 2000). The location of agents in the environment can be defined as *ex ante*, or can be made to appear in the space randomly or according to any rule. Location on the dimensions may take the form of xyz coordinates. This simulated space can represent a wide array of contexts, including organizations (Dunn and Gallego, 2010), markets (Hoffmann *et al.*, 2007), teams (Grow and Flache, 2011) or any other social or economic environment (Gilbert and Terna, 2000). Location of agents may mimic their actual location or it may represent their state of mind, physical or psychological proximity, and much more.

2.3 Rules

The ABM system works around rules that are specified in software programming. It is the social scientist that defines the "rules" that shape agents' conduct. These rules can be behavioral, interactional and time-dependent.

On the one hand, behavioral rules define what each agent is capable of doing, given their characteristics. These rules are set to program agents so that, given certain conditions, they behave accordingly. On the other hand, interactional rules define what happens to an agent or to the environment if two or more agents with certain characteristics meet, get closer or establish some connections. These rules may, for example, apply to the study of how employees react toward innovations introduced by management (Garcia, 2005). In this particular case, the interactional rule should be different depending on whether the employee deals with management or other employees (Lazaric and Raybaut, 2004). It is also possible to model processes such as routines, their formation (Miller *et al.*, 2012), or other norms in social groups (Conte and Castelfranchi, 1995; Neumann, 2010).

Finally, rules can be defined as time-dependent. These may modify an agents' characteristics, other rules or the shape of the environment as time goes by (Neumann and Cowley, 2015). A time-dependent rule is, for example, one that assumes that employees learning experience changes with time of employment (Miller and Lin, 2010). In fact, it is possible to program an algorithm that would do that to the agents.

3. Representing complex phenomena

One of the characteristics that ABMs are known for is complexity (Van Dam, Nikolic, and Lukszo, 2013). This is an "emergent" aspect of the simulation, more than something which directly originates from a line of code or from the agents (Drogoul and Ferber, 1994; Gilbert, 2008). Individual characteristics of agents and the way they interact, together with the layout of the environment and the rules, make them behave as following complex dynamics (Sutcliffe and Wang, 2012). What exactly is complexity? This article is not the place to fully discuss such an intriguing and important topic, but some insights can be succinctly provided (for an excellent review see Burnes, 2005). One aspect of complexity is the fact that phenomena emerge from the combination of its components (synergies) in a way that is not directly predictable by the study of each individual component. This aspect is clearly related to systems theory (Forrester, 1980), and is one of the elements that is clearly reflected in the use of ABMs (Miller and Page, 2007). This approach to complexity is particularly relevant for team research, as the dynamic of the group is more than the elementary sum of individual member's behavior or cognition (Thomsen, 2015; Gigliotta *et al.*, 2007). A second way to define complexity is to look at the initial conditions. When a given system's behavior or evolution cannot be predicted by the conditions initially set, then it can be defined as complex (Prigogine and Stengers, 1984). One implication of this assumption is that elements and events in the system are connected in a non-linear fashion. This is typical of social systems that adapt and partially or significantly modify initial conditions, so that predictions based solely on the initial state of the system have very limited scope (Stacey, 2003). Once again, ABMs are probably better suited to deal with this loose dependence on initial conditions in that similar initial conditions may lead to extremely different results.

Given that complexity is one of the most important features of these models, social scientists need to run the simulation multiple times before a clear pattern emerges from the data (Secchi and Seri, 2014; Ritter *et al.*, 2011). Sometimes, nothing comes out, and this points at modeling deficiencies or shortcomings of the underlying theory. This helps us highlight two implications. First, agent-based modeling overcomes some of the limits of equation-based models shifting the focus off "solution finding", and realigning on the system's evolution and dynamics. Second, ABMs are used to model many different complex phenomena so that they are also deemed to represent "complex adaptive systems" (Miller and Page, 2007). A corollary of these two arguments is that there is no need for ABMs to be based on well-structured formal theories because agents, rules and environments can be defined as the model takes shape (Secchi and Neumann, 2015). This is particularly important for our case, given that management and organizational behavior theories are seldom based on formal equations.

4. A model should be "as simple as possible – but no simpler"

One of the "mantras" of models in science is simplicity. The quote in the title of this section is attributed to Albert Einstein and it is often found in simulation and modeling articles and books. The section above highlights that social reality is complex and, therefore, may be extremely difficult to represent or model. However, it also points out that complexity is an emergent characteristic of the simulated agent-based systems. This implies that a model of a complex system may not necessarily be designed to be complex from the start. Complexity may arise from agents behaving rather simple and/or interacting with straightforwardly simple rules. In many instances, there is no need to make the model more difficult when interesting behavior may arise from keeping it simple (Coen, 2009a). How far can simplicity be taken?

In heavily math-based type of modeling, the simplicity rule is probably extremely valuable. The most important problem there is that complicated mathematical representations of reality may not indicate a solution. Put differently, some complicated systems of equations are analytically intractable and cannot be solved. This is a problem – for example, traditional computational economics is very much concerned with (Gilbert and Terna, 2000). And, here is where an ABM comes to help. As already noted, this particular category of models is not concerned with finding solutions or solving equations. Instead, it is concerned with analyzing dynamics and adaptation processes in a given system.

As many point out (Coen, 2009a, 2009b; Cioffi-Revilla, 2009; Edmonds and Moss, 2005), there seems to be a trade-off between simplicity and realism for modelers. Although some adhere to Axelrod's (1997b) KISS (Keep It Simple, Stupid) principle, there is a tension between simplicity and complexity in modeling. This depends on the trade-off between the level of abstraction that is represented in the model, as opposed to its tightness to reality. The more the model tends to address generalizability, the farther it is from reality, hence the more abstract it is, and the simpler it appears to be. Vice-versa, the more attuned to reality it is, the more complex it becomes. The ABM allows for greater complexity in the modeling stages and allows modelers to go as detailed as they wish. Of course, there is a limit to this as a perfect correspondence between the model and reality is – thus far – not achievable (Deffuant *et al.*, 2003). However, there are some examples of close representation where the simulated reality needs to be particularly complex. This is the case, for example, of a model of the impact of advertising in New York's Times Square; the streets and the advertising appear exactly as in the real world and flux of people and car traffic is also kept very close to reality (Shcherbyna, 2014). Another example is slightly more abstract, but still particularly complex and represents the evolution of the Maya civilization in South America, covering a period of pre-Colombian expansion (Heckbert, 2013). The simulation is based on a set of archeological data and assumptions on the economy, agriculture, trade and their impact on the Mayan social-ecological system.

In summary, it seems that the fears of a simulation technique not being able to capture reality are not well posited when we discuss ABMs. Given the power of this particular type of simulation, the risk is exactly that of making the model too simple. In a provocative article, Edmonds and Moss (2005) suggest that an agent-based approach supports a KIDS (Keep It Descriptive, Stupid) logic. Instead of arguing for simplicity or complexity in modeling, I am very much aligned with Coen (2009a) and suggest that the rule is tied to the "why" question. The choice of whether to use more or less simplification (or abstraction) depends on the nature of the scientific enquiry. Hence, "why" a given phenomenon is modeled should drive the choice. With ABMs, the new element is that there are limitless solutions to the range of simpler to more complex assumptions for any given model. Although they are not organization-based, the examples above are particularly clear on this point in that reproduction of an environment (e.g. Times Square in New York) is necessary if that is what is implied by the particular modeling effort. Simpler solutions should not be excluded a priori, though.

What this means is that we can question whether the "motto" that appears in the title of this section still holds. The ABM should be as simple or as complex as the research question asks it to be. This also means that it is probably time for social sciences to abandon idealistic references to the "hard" sciences. Of course, more elegant solutions should always be welcome, but this is not a necessity any more. As some have argued before, complex reality requires complex modeling […] until science finds a way to synthesize complexity in simple effective forms (Van Dam *et al.*, 2013; Edmonds and Moss, 2005).

5. User-friendly simulations

One of the most significant drawbacks of simulation techniques is that they usually require programming skills. This is to be built on top of the many research skills that social scientists have in their toolkit. This need for software programming has made simulation less appealing to management and organizational scholars. IBM's Statistical Package for the Social Sciences (SPSS) makes it easier for most scientists to use statistics in their analysis. The platform is intuitive, user-friendly and exploits computational power very effectively. Although an equivalent to SPSS is not yet available, there are options that make agent-based computer simulation easier.

As Fioretti (2013) points out, there are a number of platforms that make agent-based simulation more user-friendly and easy to use than most of the other simulation techniques. There is a plethora of ABM simulation tools, including but not limited to: NetLogo, RePAST, AnyLogic, Jason, Mason, MadKit, Brahms and Cormas (for a more comprehensive list of platforms, see Nikolai and Madey, 2009). These "platforms" are not code-free; they still require some programming to be completed by users. However, I believe the difference here is in the fact that some of these software present a user-friendly interface and the programming language is not overly complicated and it is, in fact, rather intuitive. I focus very shortly on three of these modeling platforms that present these characteristics, i.e. NetLogo, RePast and AnyLogic.

5.1 NetLogo

This software was created by Wilensky (1999) and his team at Northwestern University in the USA. The software can be downloaded for free, although its source code is not available (Nikolai and Madey, 2009). It uses "Logo", a programming language that is relatively easy to learn and use and also offers a user-friendly interface where buttons, sliders and graphs can be easily created to observe agents' behavior, to monitor and to adjust the simulation. Due to its flexibility, an extensive online support that includes many models, and very good start-up instructions, this is one of the most widely used platforms (Thiele *et al.*, 2012).

5.2 RePast
This simulation suite is another very popular platform that is available online to download for free. The source code is made available by RePast's authors under the Berkley Software Distribution license. Originally developed at the University of Chicago, this platform allows for multiple programming languages, including a dialect of Logo (ReLogo), Java, general visual programming, Python (Nikolai and Madey, 2009). The Web site offers several tutorials, access to some models and several other services.

5.3 AnyLogic
Some of the platforms are built on proprietary software and AnyLogic is one of them. I have selected it among the many others because it offers a powerful graphic interface, capable of representing the real world in granular details. When the purpose of modeling is more tied to reproducing a given environment or when behavior/interactions happen in a context that needs to be replicated in its original form or shape, then this software can be successfully used. Also, as a significant addition in comparison to the other platforms, the company that licenses the software claims that AnyLogic combines system dynamics, discrete events and agent-based techniques together. The programming language for this platform is different from the other two and from most platforms and it is called unified modeling language for real time (UML-RT; Nikolai and Madey, 2009).

This very succinct review of simulation tools shows that there are a number of platforms for ABMs. Despite the need to learn a programming language, today the task of the modeler is made much easier than it was only 20 years ago. However, it is clear that the knowledge required to operate one of these platforms is more intense than the statistics needed to make SPSS work.

6. When and how to use ABMs

One of the uses of ABMs is that of assessing or evaluating how sound a theory is, in a process where thought experiments can be run and attain further confirmation or discard a given aspect of existing or new theory (Bardone, 2015). In addition to a more "traditional" use of ABMs, some have started to compare them with quantitative research, as a sort of validating procedure (Edmonds and Moss, 2005) that some may call triangulation (Coen, 2009b). The model can be built as a result of a quantitative study or, the other way around, data can be used to validate the model (i.e. as a check that the model is not over-or under-shooting). In addition to these two obvious references to quantitative and theoretical use of ABM, some have suggested that they can also be used in combination to qualitative research (Janssen and Ostrom, 2006) or even anecdotal information (Edmonds and Moss, 2005). This "softer" research tradition can be used – and it is often used very informally by modelers – to identify the parameters and relationships that can be simulated in an ABM. The interesting point is that this technique is versatile enough so that there is no need to choose between using it for theory development, validation or anything else.

A slightly different question can be asked on what ABMs should not be used for. One particular set that does not suit this technique very well is that of models where there is a deterministic solution to the problem (Coen, 2009a). If that is the case, then equations or other more traditional techniques can be successfully used.

7. Increasing popularity

There are a number of fields that are making increasing use of ABM (Heath *et al.*, 2009). In this subsection, I focus on resources available for organizational and team research.

In the past two decades, the top ten management journals (endnote 1) published articles that referred to ABM anywhere in the text only 12 times (0.03 per cent), with no occurrences before 1999. If "agent-based" (and combinations) is searched as a keyword, it never appears connected to any article. Given the claim made at the beginning of this paper, this is not surprising. In short, top tier journals are not the source where one should look for ABM or any other kind of computational modeling. Other more specialized journals may be more open to innovative and forward-looking techniques. A quick look at team-related journals (endnote 3) reveals that "agent based" and its variations appear 97 times, equivalent to 3.1 per cent of the total number of articles published in the years 1994-2013. This is about ten times of what is found for the top ten management journals. Most of the occurrences (90) are obviously from *Group Decision & Negotiation*, a journal of the Institute for Operations Research and the Management Sciences. *Team Performance Management* has recently published two articles that are based on multi-agent simulations (Ekmekci and Casey, 2011; Breuer *et al.*, 2013), *de facto* opening the door to the use of ABM in team research.

Two journals focus on quantitative modeling and simulation techniques for the social and organizational sciences. *Computational and Mathematical Organization Theory* (*CMOT*) is a USA journal founded in 1995 and devoted to publishing research that adapts formal mathematical techniques to the study of organizations and society (Carley and Wallace, 1995). On the occasion of its inclusion to the Social Science Citation Index, the editorial team wrote about developments and better specified where the journal stands among others. They define the character of the journal as multi-disciplinary (Meyer *et al.*, 2011). Also, using citation analysis, they show that articles published in *CMOT* cite management journals more often (19.9 per cent) than those from other social science disciplines, i.e. sociology (14.5 per cent), business (9.6 per cent) and economics (8.4 per cent). By means of co-citation analysis they reveal that the areas covered in the period 2002-2008 are "organizational design and teams", "learning and feedback" and "social networks and organizational ecology" (Meyer *et al.*, 2011, p. 17). Far detached from these first areas is "agents and social norms" (Meyer *et al.*, 2011, p. 19). Running a search with the keyword "agent-based" reveals there are 123 articles that appear between 2007 and 2013 using the terms somewhere in the article. While it is hard to reach a definitive conclusion about this finding, it seems that *CMOT* publications have only recently started to focus more on an ABM.

Another source is the *Journal of Artificial Societies and Social Simulation* (*JASSS*), a European journal founded in 1998. Articles are available online free of charge for everyone to search, read and/or download. Citation analysis (Meyer *et al.*, 2009) shows that the first cited areas are economics (13.1 per cent), sociology (5.8 per cent) and management (3.4 per cent). The more regularly cited macro subject categories of the Institute of Scientific Information are economics and management (21.0 per cent), sociology (10.4 per cent), computer science (8.2 per cent) and psychology (7.7 per cent). The composition for this journal is slightly different from that of *CMOT* in that sociology and economics publications seem to be more prevalent. However, the emphasis of *JASSS*, while sharing similar aims and scope to that of *CMOT*, is mostly directed toward simulations. In fact, a co-citation analysis (Meyer *et al.*, 2009) shows that the area "cognitive agents within organizational structures" (Meyer *et al.*, 2009, s. 4.8) features some of the most cited articles in the years 2003-2007. A quick check of how many times "agent-based" (or combinations) appeared in the titles of articles published in the period 1998-2013 reveals 192 hits, with "multi-agent" (or combinations) occurring 53 times. The appearance of these words increases after 2005, with 79 hits from 1998 to 2005, and 166 hits between 2006 and 2013. Here too, it is apparent that ABM is increasing its presence among *JASSS* published articles.

In summary, what management scholars can deduce from these findings is that *JASSS* and *CMOT* are compelling resources for those wishing to explore the worlds of modeling and simulation. *CMOT* is a good reading for those focusing more on organizational aspects, while *JASSS* offers ideas and support, specifically on modeling and agent-based simulations.

8. Conclusions

The paper has described ABM as a computational technique that may help organizational behavior scholars deal with some concerns they traditionally have over simulation studies. One paper is not enough to show how ABM can really impact management studies. However, this work has given some examples of work published in the area that have employed an ABM to tackle management issues (e.g. teams, innovation, learning and cognition). This paper has also shown that ABM is an extremely flexible technique and can be used as an aid to qualitative and quantitative techniques, as well as theory development. The insights deriving from the use of these models are more compelling when (a) most units in the social system are capable of relatively autonomous behavior, (b) the phenomenon is better described as bottom-up, (c) interactions and synergies among units lead to some emergent properties of the system, (d) the system is largely unpredictable (light dependence on initial conditions) and (e) there is a need for granularity. This list is not comprehensive; nevertheless, it provides some support for the central idea presented in this paper that ABM may actually increase our understanding of management and organizational behavior.

These models are not without limits in that they can be misused and their results misinterpreted. There are almost two significant limitations. The first is that parameter configurations depend on subjective interpretations of the modeler; hence, there is a risk of inaccuracy or, worse, bias. The second is that results may not be easy to interpret or to connect to what was originally modeled, giving the impression that the ABM is an esoteric black box. Seen from this angle, an ABM is no different from other modeling and simulation techniques. However, this article shows that agent-based approaches are probably better positioned than others to tackle with most of organizational scholars perplexities on computer simulation.

As far as team research is concerned, an ABM offers support at both the micro/individual and the meso/group level, with opportunities to also fit in the organizational or macro level. Whether researchers would like, for example, to compare a simulated team with a real team (Thomsen, 2015), or to analyze the complex patterns of team dynamics via identification, socialization, perception (Ekmekci and Casey, 2011), or to explore how social interactions emerge and adapt due to skills, competences and roles within a team, agent-based simulation may reveal to be a valuable tool. It is the ability to analyze emergence as a key characteristic that stems out of complex adaptive systems that makes ABM a key for team research.

Finally, there are relatively simple and user-friendly platforms for these types of computational models and, fourth, their bottom-up, adaptive and dynamic perspective makes it easier to understand when these models are more suitable to the analysis.

Notes

1. They are: *Academy of Management Annals*, *Academy of Management Review*, *Academy of Management Journal*, *MIS Quarterly*, *Journal of Management*, *Journal of Operations Management*, *Administrative Science Quarterly*, *Journal of Applied Psychology*, *Strategic Management Journal*, *Personnel Psychology*. *Academy of Management Annals* (AMA) and *Organizational Research Methods* (#11 in the list) were excluded because they do not cover the 20-year period. Next in line is the *Journal of International Business Studies*, included in the list of ten. The search was performed using BSCO.
2. *The Journal of Operations Management* does not publish many math or simulation articles, respectively, 9 and 10 (0.8 per cent and 1.1 per cent of the total number of articles published) in 1994-2013.
3. Selected journals due to popularity (SJR's Scimago): *Team Performance Management* (1995), *Small Group Research*, *Group Dynamics* (1997), *Group Processes* and *Intergroup Relations* (1998), *Group and Organization Management*, *Group Decision and Negotiation*.

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